APPLICATION FOR
LETTERS PATENT OF THE UNITED STATES

SPECIFICATION

To all whom it may concern:

Be It Known, That we, MARK N. SMYTH, SIAMAK SAFARIAN and EJAZ HAIDER, of Innisfil, ON, Canada, Richmond Hills, ON, Canada and Markham, ON, Canada, respectively, have invented certain new and useful improvements in METHODS AND SYSTEMS FOR TUNING SEASONAL DEMAND FORECASTS FOR PRODUCTS, of which we declare the following to be a full, clear and exact description:

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METHODS AND SYSTEMS FOR TUNING SEASONAL DEMAND FORECASTS FOR PRODUCTS

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CROSS REFERENCE TO RELATED APPLICATIONS

This application is related to the following co-pending and commonly-assigned patent application, which is incorporated by reference herein:

Application Serial No. ___________, entitled "METHODS AND SYSTEMS FOR FORECASTING SEASONAL DEMAND FOR PRODUCTS HAVING SIMILAR HISTORICAL SELLING PATTERNS," by Edward Kim, Roger Wu, Frank Luo and Andre Isler; attorney docket number 11,402; filed on December 1, 2003.

FIELD OF THE INVENTION

The present invention relates to methods and systems for forecasting product demand for retail operations, and in particular to the tuning of seasonal demand forecasts for products.

BACKGROUND OF THE INVENTION

Accurately determining demand forecasts for products are paramount concerns for retail organizations. Demand forecasts are used for inventory control, purchase planning, work force planning, and other planning needs of organizations. Inaccurate demand forecasts can result in shortages of inventory that are needed to meet current demand, which can result in lost sales and revenues for the organizations. Conversely, inventory that exceeds a current

demand can adversely impact the profits of an organization. Excessive inventory of perishable goods may lead to a loss for those goods, and heavy discounting of end of season products can cut into gross margins.

Inferior forecasting science and gut feel decisions on inventory have created significant stock-out conditions across the industry. Recent studies quantify stock-outs in the retail industry at 5 to 8%, while overstock conditions caused by poor forecasts and buys continue to climb.

This challenge makes accurate consumer demand forecasting and automated replenishment techniques more necessary than ever. A highly accurate forecast not only removes the guess work for the real potential of both products and stores/distribution centers, but delivers improved customer satisfaction, increased sales, improved inventory turns and significant return on investment.

Teradata, a division of NCR Corporation, has developed a suite of analytical applications for the retail business, referred to as Teradata Demand Chain Management, that provides retailers with the tools they need for product demand forecasting, planning and replenishment. As illustrated in Figure 1, the Teradata Demand Chain Management analytical application suite 101 is shown to be part of a data warehouse solution for the retail industries built upon NCR Corporation's Teradata Data Warehouse 103, using a Teradata Retail Logical Data Model (RLDM) 105. The key modules contained within the Teradata Demand Chain Management application suite 103, organized into forecasting and planning applications 107 and replenishment applications 109, are:

Demand Forecasting: The Demand Forecasting module 111 provides store/SKU (Stock Keeping Unit) level forecasting that responds to unique local customer demand. It continually compares historical and current demand and utilizes several methods to determine the best product demand forecast.

Seasonal Profile: The Seasonal Profile module 113 automatically calculates seasonal selling patterns at all levels of merchandise and location, using detailed historical sales data.

Contribution: Contribution module 117 provides an automatic categorization of SKUs, merchandise categories and locations by contribution codes. These codes are used by the replenishment system to ensure the service levels, replenishment rules and space allocation are constantly favoring those items preferred by the customer.

Promotions Management: The Promotions Management module 119 automatically calculates the precise additional stock needed to meet demand resulting from promotional activity.

Automated Replenishment: Automated Replenishment module 121 provides suggested order quantities based on business policies, service levels, forecast error, risk stock, review times, and lead times.

Allocation: The Allocation module 123 determines distribution of products from the warehouse to the store.

Good forecasts are the product of accurately modeling trend, seasonality, and causal effects. Of these three factors seasonality is the most influential in producing accurate forecasts. The Teradata Demand Chain Management solution described above provides a retailer with improved customer service levels and reductions in unproductive inventory, and is particularly adept at assisting a retailer forecast and plan for seasonal sales cycles. For many products, demand varies a great deal, depending on the time of year., e.g., snow shovels. This seasonal variation, referred to as the product's seasonal profile, may vary greatly for different products. For example, the demand patterns for sun tan lotion and lawn and garden equipment looks considerably different than the demand patterns

for snow tires, school supplies or cold medication. To obtain an accurate forecast for a given item, seasonality must be taken into account. In fact, seasonal profiles are responsible for over 50% of the accuracy of a product's forecasted demand. Inaccurate forecasts can result in an overstock of slow moving products and out-of-stock situations for items during peak demand times.

In order to reduce noise, increase accuracy and improve forecasting efficiency, seasonal profiles are typically calculated at an aggregated level or class of the merchandise or product hierarchy. This methodology presumes that the individual products in the aggregated level have a similar seasonal selling pattern. However, not all products in a given class may have the same seasonal selling pattern. Therefore, there exists a need for improved demand chain forecasting tools that provide retailers with a methodology for analyzing product seasonal selling profiles and sensibly associating products with group seasonal models that more accurately model the products' sales activity, thereby increasing product demand forecast accuracy.

SUMMARY OF THE INVENTION

It is an object of the present invention to provide a new and useful system and method for associating products with product seasonal models for use in forecasting future product sales for a retailer.

It is a further object of the present invention to provide such a system and method for associating products with product seasonal models that examines variances between historical product sales patterns and product seasonal models and realigning products with the seasonal models determined to provide the best match for the products.

The system collects and stores within a database a minimum of one year of historical weekly demand data for products sold by a retailer. Each products is

associated with one of several different seasonal models utilized for forecasting future product sales. Each seasonal model represents an annual sales pattern for the products associated therewith. The system compares the historical weekly sales data for products with the different seasonal models to determine a best match between products and seasonal models, and when a better fit is discovered, a product's association is changed to the seasonal model determined to provide the best match for the product.

Other aspects of the present invention will become apparent to those skilled in the art from the following description of various embodiments. As will be realized the invention is capable of other embodiments, all without departing from the present invention. Accordingly, the drawings and descriptions are illustrative in nature and not intended to be restrictive.

BRIEF DESCRIPTION OF THE DRAWINGS

Figure 1 provides an illustration of a forecasting, planning and replenishment software application suite for the retail industries built upon NCR Corporation's Teradata Data Warehouse.

Figure 2 provides an illustration of an exemplary merchandise hierarchy for a department store.

Figure 3 provides a bar graph displaying seasonal factors for a retail product for a fifty-two week fiscal year.

Figure 4 provides a line graph comparing the seasonal sales models for two product groups with the individual seasonal sales model for an individual product within one of the two product groups.

Figure 5 provides a flow diagram illustrating a process for automatically identifying products and group sales models having dissimilar sales profiles and

re-associating products to more suitable group sales models in accordance with the present invention.

DETAILED DESCRIPTION OF THE INVENTION

In the following description, reference is made to the accompanying drawings that form a part hereof, and in which is shown by way of illustration specific embodiments in which the invention may be practiced. These embodiments are described in sufficient detail to enable one of ordinary skill in the art to practice the invention, and it is to be understood that other embodiments may be utilized and that structural, logical, optical, and electrical changes may be made without departing from the scope of the present invention. The following description is, therefore, not to be taken in a limited sense, and the scope of the present invention is defined by the appended claims.

The Teradata Demand Chain Management solution described above and illustrated in Figure 1 provides a retailer with improved customer service levels and reductions in unproductive inventory, and is particularly adept at assisting a retailer forecast and plan for seasonal sales cycles. As stated earlier, seasonal profiles are typically calculated at an aggregated level or class of a merchandise or product hierarchy. Typically, a retailer maintains a merchandise hierarchy wherein goods and services provided by the retailer are grouped together by common characteristics, for example, women's fashion, office equipment, or kitchen products. These groups are used as the basis for inventory management, planning, controlling, profitability analyses, and evaluations.

Merchandise categories allow a retailer to classify and structure the entire range of goods offered for sale by the retailer. Every product or service is assigned to a single merchandise category across a whole company. Merchandise categories can be assigned to stores and store departments. A successfully

implemented merchandise category hierarchy is an essential tool for efficient merchandise category management.

Figure 2 provides an illustration of an exemplary merchandise hierarchy for a department store. Three levels of a merchandise hierarchy are illustrated, with each lower level in the hierarchy containing more specific product groupings. The topmost level of the hierarchy, class 1, includes the broad product categories Men's Wear 210, Women's Wear 220, Children's Clothing 250, Home Décor 260, Kitchen/Bath 270 and Consumables 280. Portions of a second level of the hierarchy, identified as class 2, are illustrated for the Women's Wear 220 and Consumables 280 class 1 product categories. Class 2 product categories under Women's Wear 220 include Women's Outerwear 225, Women's Underwear 230, Women's Sleepwear 235 and Women's Accessories 240. Class 2 product categories under Consumables 280 include Pet Products 285 and Eyewear 290.

Example class 3 product categories are provided under each of the class 2 categories shown. For example, class 3 product categories included in Women's Outerwear 225 include Women's Coats 227, Women's Blouses 228 and Women's Slacks. The class 1, 2 and 3 categories shown in Figure 2 are for illustration only. An actual merchandise hierarchy for a retail business may or may not include the merchandise classes and groups illustrated, and may include additional merchandise categories not shown. Additional, more specific, merchandise class categories may be included below class 3. All products offered for sale by the retailer are represented within at least one of the lowest level merchandise class categories within the merchandise hierarchy.

As part of the demand forecasting process, historical demand data is saved for each product or service offered by a retailer. This historical demand data, and other information derived therefrom, may be obtained for an individual product and also for all products within a merchandise group. As stated earlier, the

demand forecasting process utilizes seasonal profiles or models that are typically calculated at an aggregated level or class of the merchandise or product hierarchy. This methodology presumes that the individual products in the aggregated level have a similar seasonal selling pattern, which may not always be accurate.

The seasonal profile, or model, for a product or product grouping is determined by calculating an Average Rate of Sale index called a Seasonal Factor for each week of the fiscal year. A Seasonal Factor is calculated relative to an average week weight (1.0). For example, a Seasonal Factor of 2.0 means that sales for the measured period are expected to be twice that of an average period. Figure 3 provides a bar graph displaying seasonal factors for a retail product for a fifty-two week fiscal year that begins with the first week in July. The product in this example graph is an artificial Christmas tree. As one would expect for a seasonal product such as this, sales are concentrated in the weeks just prior to Christmas, which occurs in week 26. Very few sales are seen to occur in the weeks in January through September. Seasonal factors range from near 0, during many of the weeks from Weeks 1 through 10 (July through September) and Weeks 28 through 52 (January through June), to a high of over 9.0 in Week 19.

Seasonal profiles may be displayed graphically by line graphs, such as in Figure 4. Figure 4 provides a comparison between the seasonal sales models for two different product groups, depicted by line graphs 401 and 403, and a seasonal sales model for an individual product, shown by line graph 405. In this example, graph 401 represents the seasonal profile for a product group including children's toys, graph 403 represents the seasonal profile for the product group including pet products, and graph 405 represents the seasonal profile for a pet toy.

Typically, pet toys would be aggregated into the pet product grouping for demand chain forecasting. However, the seasonal profile for the pet toy shown in graph 405 corresponds more closely with the seasonal profile for the children's

toys product group, shown by graph 401, than with the seasonal profile for the pet products group, shown by graph 403. Graphs 401 and 405 are seen to be very similar, with corresponding peaks and valleys, and no substantial variance between the Seasonal Factors of the product group graph 401 and the product graph 405 during any specific week. The example seasonal profile graphs of Figure 4 show a product that is more properly included, for demand forecasting purposes, in the seasonal profile represented by graph 401, rather than the seasonal profile represented by graph 403.

A bad fit between a product and its model may result in bad forecasts and the potential of inventory shortages or dollars misspent. The importance of accurate models, therefore, cannot be over stated. Figure 5 provides a flow diagram illustrating a general process for automatically identifying products and group sales models having dissimilar sales profiles and re-associating products to more suitable seasonal models. This process, referred to herein as Automatic Profile Tuning (APT), is employed to manage those products that are not well represented by their original model's seasonality.

Automatic Profile Tuning examines the variance or difference between the seasonal factors for a product and the corresponding seasonal factors for its model. APT looks for exceptions. If the product's seasonal factor variance exceeds preset limits, APT seeks a better model for that product, i.e., a model with a lower variance to the product. This is an iterative process, the goal of which is to reduce the variance between products and their corresponding models. In turn, the results increase forecast accuracy, inventory productivity and sales.

Referring now to Figure 5, the major elements of a batch process for automatically tuning product seasonal models will know be described. To tune products using APT, the user must submit a tuning session, including desired tuning parameters, to the APT batch process. The APT batch process will only

tune the products that are in the classes or models and locations defined for the session. Tuning process input parameters and user-defined limits, filters and requirements are contained in the table PFAutoTuningHeader 501. Tuning parameters specified in table PFAutoTuningHeader 501 include:

Tune SKUs with an ARS >= The APT batch will tune all products that meet Location and Classification criteria, and have a current Average Rate of Sale equal to or greater than the value in this field.

Model Variance >= Model Variance is an overall measure of how well the Model is representing the products that are currently in the mode. The larger this value, the less representative is the model, and the greater the need to analyze the products contained in the model for possible regrouping.

SKU Tuning Variance >= The difference between the seasonal factors for a product and the seasonal factors for its model. When evaluating model suitability, APT looks for products with a seasonal factor difference variance that is equal to or greater than this value. These products are then flagged for tuning.

SKU Acceptance Variance <= This value specifies the tolerance acceptable to the user for moving products to better fitting models. If the variance of the product to the best fitting model the APT batch can find is less than or equal to this value, the product will be tuned to the best fitting model. SKU Acceptance Variance must be less than the SKU Tuning Variance.

SKU Acceptance Difference >= This value specifies the tolerance acceptable to the user for moving products to better fitting models. If the difference between the variance of the product to its current model and the variance of the product to the best fitting model the APT batch can find is greater than or equal to this value, the product will be tuned.

A model list is composed in step 503, applying the tuning parameters contained in table 501, with the resultant list saved to table PFAutoTuningDetail 505. The models identified in table 503 are examined, and those models having a variance greater than a preset Model Variance Limit are eliminated from further consideration. These high variance models are saved to a table 509 named PFHighVarianceModels. Models with variance below the Model Variance Limit are saved to a temporary table 511.

In step 513, products submitted for tuning are examined to eliminate from consideration those products with a low average rate of sales (ARS) or those products with an insufficient sales history, i.e., less than 52 weeks of sales history. A list of products passing this examination is saved to a temporary table 515.

In step 517, the seasonal factors for each product listed in table 515 are compared with the seasonal factors for the models listed in table 511 to identify the model providing the highest correlation between the seasonal factors for the product and the corresponding seasonal factors for the models, i.e., lowest variance between product profile and model. In addition to the seasonal models created automatically by the demand chain management profile module, standard models created manually by the user may be included in the comparison.

In step 519, the products and corresponding best-fit models identified in step 517 are examined to determine if the variances between product profiles and models are below an acceptable variance level. A record of each product without an acceptable best-fit model is saved to database table PFUnMatchedProducts 521. A high variance summary report may be produced from the information contained in table 521, as shown in step 525. Summary results are saved to table PFHighVarSummary 525.

Products identified in step 519 as having acceptable best-fit models, different from their currently associated models, may be moved to their newly

identified best-fit models. A record of product moves is kept in table PFMoveHistory 527.

Although the flow chart of Figure 5 illustrates a method for identifying products that are "out-of-tune" and re-associating out-of-tune products with more compatible models, tuning can also be carried out to adjust a product or model's demand to change seasonality; to tune a model; or to create models for regrouping.

Conclusion

The Automatic Profile Tuning (APT) process described above is an enhancement to current demand chain forecasting applications that provides to a user the ability to automatically tune seasonal models used in demand chain forecasting. The APT process automatically recommends the movement of products to more suitable seasonal models, produces reports so that the user can track what the module is doing, and identifies high variance products and models that need special attention.

The foregoing description of various embodiments of the invention has been presented for purposes of illustration and description. It is not intended to be exhaustive nor to limit the invention to the precise form disclosed. Many alternatives, modifications, and variations will be apparent to those skilled in the art in light of the above teaching. Accordingly, this invention is intended to embrace all alternatives, modifications, equivalents, and variations that fall within the spirit and broad scope of the attached claims.